

Distributed Localization Scheme for Robots Based on Wireless Sensor Networks

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Abstract-Localization is an essential and important research issue for robots, in this paper, we propose distributed localization scheme for robot based on WSNs (wireless sensor network). In the WSNs, robots act as mobile nodes, so the location method for WSNs' nodes can be used for robots. Range-based location method and range-free location method are discussed in detail in the paper.

Keywords-localization; robot; wireless sensor networks; Monte Carlo algorithm

I. INTRODUCTION

Localization is the problem of determining the pose of a robot [1]. In order to achieve more sufficient accuracy, many localization schemes are proposed [2-5]. In these schemes, the robot must acquire a large amount of information from several types of sensors. A disadvantage is that the powerful processing units will need consistent power supplies and the accuracy will degrade. Another drawback of using sensors is given by the fact that it is difficult to represent correctly and in all details the environment and position of robot due to errors in the data collected by the sensors.

Recent years, wireless sensor networks (WSNs) is emerging as a key tool for data acquisition in many applications [6,7], they can be utilized in a wide range of areas, such as environmental monitoring, chemical or biological agent detector, machine monitoring, medical care, intelligent buildings, disaster prevention, inventory tracking, traffic monitoring and military surveillance. In many applications of WSN, node localization is important to network monitoring, tracking, targeting and surveillances. The original idea to localize sensor node is using a Global Positioning System (GPS) on every sensor node. But considering the cost and power consumptions, the GPS solution is not acceptable in many applications. Many people suggest using some special sensor nodes, namely anchor nodes, which already know their absolute locations. Other sensor nodes estimate their locations based on the information provided by these anchor nodes.

In this paper, we present a solution for mobile robot location based on wireless sensor networks. In this solution, mobile robots are treated as a WSNs' nodes. So we can use current methods of node localization of WSNs. Actually, many localization algorithms have been proposed for WSNs[7]. In general, these algorithms can be divided to two groups of centralization and distributed methods. Centralized methods must send data to central station that do not fit the robot location. Therefore we will focus on the distributed

localization method.

In distributed methods, each node estimates its position based on association with its adjacent nodes. These methods can be classed two categories: range-based localization and range-free localization schemes. This classification is made according to whether it needs to know the real range between nodes or not. The ranged-based algorithms need to measure by means of additional hardware the distance or angle between each node in order to determine its geographical position, the ranging knowledge can be obtained using different kinds of ranging techniques, for example: Received Signal Strength Indicator (RSSI) [9], Time of Arrival (TOA) [10], Time Difference of Arrival (TDOA) [11] and Angle of Arrival (AOA) [12]. Instead of real ranging, range-free algorithms use the network constraints such as connectivity or anchor nodes information to estimate the coordinates of the nodes [8,13, 14].

In the next section, we discuss the mobile robot localization in range-based WSNs. In section 3, the range-free WSNs for mobile robot localization system and algorithms were discussed. Finally, section 4 concludes this paper.

II. ROBOT LOCALIZATION IN RANGE-BASED WSN

A. System Overview

In the system, the robot node can walk freely, and the other nodes are static which provide environment information to robot node. These nodes commonly are employed ahead, and those positions are known. These nodes are called beacon nodes. The distance information between robot node and beacon can be got in different methods, such as time of arrival (TOA), angle of arrival of signals (AOA), received signal strength to nodes (RSS), and the different between the arrival times of two different signals (TDOA).

B. Fundamental Algorithms

In this system, there are two level position computing: coarse-grained localization and fine-grained localization.

Centroid calculation is a coarse-grained localization. Consider a two-dimensional scenario. Let there be n reference nodes detected within the proximity of the robot node, with the location of i th such reference denoted by (x_i, y_i) . Then in this method, the location of the unknown robot node (x_r, y_r) is determined as

$$(x_r, y_r) = \left(\frac{1}{n} \sum_{i=1}^n x_i, \frac{1}{n} \sum_{i=1}^n y_i \right) \quad (1)$$

If the bounds on radio or other signal coverage for a robot node is circle of radius, so we can calculate the centroid of the shape which is the coverage of beacon nodes for robot node, as shown in Figure.1

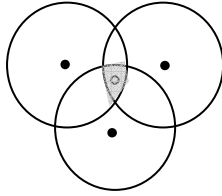


Figure.1 Localization using intersection of circle constraints

One of the nice features of these methods is that not only can the robot nodes use the centroid of the overlapping region as a specific location, but they can also determine a bound on the location error using the size of this region.

Triangulation distance estimates is a fine-grained localization method. The location of the unknown robot node (x_r, y_r) can be determined based on measured distance estimates \hat{d}_i to n reference nodes $\{(x_1, y_1), \dots, (x_i, y_i), \dots, (x_n, y_n)\}$. This can be formulated as a leased squares minimization problem.

Let d_i be the correct distance to the n reference nodes,

$$d_i = \sqrt{(x_i - x_r)^2 + (y_i - y_r)^2} \quad (2)$$

Thus the difference between the measured and real distance can be repressed as

$$e_i = \hat{d}_i - d_i \quad (3)$$

The leased squares minimization problem is then to determine the (x_r, y_r) that minimizes $\sum_{i=1}^n (e_i)^2$. This can be linearized by subtracting the last row, resulting in a system of

$$Ax = b \quad (4)$$

With

$$A = -2 \begin{bmatrix} (x_1 - x_n) & (y_1 - y_n) \\ (x_2 - x_n) & (y_2 - y_n) \\ \vdots & \vdots \\ (x_{n-1} - x_n) & (y_{n-1} - y_n) \end{bmatrix}, \quad x = \begin{bmatrix} x_r \\ y_r \end{bmatrix}$$

$$b = \begin{bmatrix} d_1^2 - d_n^2 - x_1^2 + x_n^2 - y_1^2 + y_n^2 \\ d_2^2 - d_n^2 - x_2^2 + x_n^2 - y_2^2 + y_n^2 \\ \vdots \\ d_{n-1}^2 - d_n^2 - x_{n-1}^2 + x_n^2 - y_{n-1}^2 + y_n^2 \end{bmatrix}$$

There are different ways to solve the fundamental linear problem. The classical way to proceed is to solve the normal equation

$$A^T X \hat{x} = A^T b \quad (5)$$

with the methods of linear algebra.

III. ROBOT LOCALIZATION IN RANGE-FREE WSN

A. System overview

Recently, in emerging applications, sensor nodes may move after deployment. In this system, all nodes are mobile nodes. So the localization of robot nodes is a dynamic process. Current methods proposed for localization of WSNs have been considering the nodes statically. For mobile node localization, Monte Carlo localization algorithm is suited this scene.

B. Monte Carlo Algorithms

Monte Carlo localization algorithm for mobile wireless sensor networks uses Sequential Monte Carlo (SMC) method [3]. The Sequential Monte Carlo method provides simulation based solutions to estimate the posterior distribution of nonlinear discrete time dynamic models.

We consider a wireless sensor network in which both the beacon nodes and the sensor nodes can move. We assume the motion is markovian, i.e., a sensor node's future position is only determined by its current position and is independent with its past positions. Assume the time is divided into discrete time units.

The key idea of Monte Carlo localization for mobile wireless sensor networks is that showing the posterior position distribution of a node using a set of weighted samples. Totally the mobile localization problem is expressed in this way that if t indicates discrete time, l_t shows the distribution of nodes location at time t . Also o_t is the observations of node from beacon nodes that received between time t and $t-1$. A transition function $p(l_t | l_{t-1})$ predicts the current position of the node based on the previous position. An observation function $p(o_t | l_t)$ also indicates based on new observations that if a position is acceptable or not. The Monte Carlo localization (MCL) algorithm calculates these sample sets recursively in each interval and by averaging these sample sets, calculates the robot nodes position.

In the Monte Carlo algorithm, robot nodes are determined in two steps: prediction and filtering. In the prediction phase, it is assumed that the node is not aware of its direction and moving speed and only knows that its maximum speed is equal

to v_{\max} . Thus the new position of node will inside a circle centered at radius v_{\max} that is shown

$$p(l_t|l_{t-1}) = 1/\pi v_{\max}^2 \quad \text{if } d(l_t, l_{t-1}) < v_{\max} \quad (6)$$

$$p(l_t|l_{t-1}) = 0 \quad \text{if } d(l_t, l_{t-1}) \geq v_{\max}$$

In the filtering phase, the robot node deletes impossible calculated position based on the new observations. To reach the goal, robot node used data of one-hop and two-hop beacon nodes that is shown in Figure.2

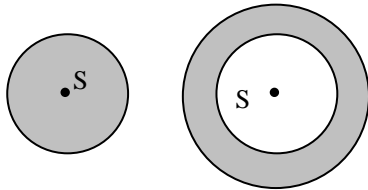


Figure.2 One hop (left) and two hop (right) beacon nodes

For all of calculated positions, a filtering condition function is run that showed in below.

$$filter(l) = (\forall s \in S, d(l, s) \leq r) \wedge (\forall s \in T, r < d(l, s) \leq 2r) \quad (7)$$

Where S shows the set of one hop beacon nodes that heard by the robot node, and T shows the set of two hop beacon nodes that can not be heard by the robot node, but heard by neighbors of the node.

Predication and filtering phases must be repeated until the desired number of samples obtained. Finally the position of robot in the time t is the average of possible locations in the sample set. The equation is

$$l_t = \sum_{i=1}^N l_t^i / N \quad (8)$$

Where, N is the number of samples.

In order to complete the sample set in the MCL algorithm, very large number of sampling attempts is needed. To resolve this problem, we use an approach called particle filter because it is simple and easy to implement. In this approach, the distribution is represented with a set of N weighted samples

$$p(l_t | o_{1 \dots t}) \approx \{ \{ l_t^{(i)}, w_t^{(i)} \} \}_{i=1 \dots N} \quad (9)$$

Where $l_t^{(i)}$ is a sample of this distribution and $w_t^{(i)}$ is its normalized weight $\left(\sum_{i=1}^N l_t^{(i)} = 1 \right)$.

Figure.3 shows a generic framework of MCL localization algorithms. There are three steps in the algorithm: initialization, importance sampling, and filtering. In the initialization step, N samples are randomly drawn from the deployment area. In time unit t , in the importance sampling step, candidate samples are drawn based on the samples in the

previous time unit and their weights are computed using the observations collected in time unit t . In the filtering step, samples with weight 0 are filtered out. The importance sampling step and the filtering step may repeat several times in order to obtain enough number of candidate samples with weight greater than 0. Then N samples are selected from these candidate samples and their weights are normalized. At last, the weighted average of the N samples is used as the estimation of a sensor node's position in the current time unit.

IV. ROBOT LOCALIZATION IN ROOM BASED ON WSN

In this case, we localize robot *EDU*, which can receive ultrasonic signal. Figure.4 shows the robot.

We carry out the robot location based on range-based scheme. In the room, there are 10 ultrasonic sensor nodes settled on ceiling in different spot as anchor nodes. Figure5 shows the anchor nodes on the ceiling. The ultrasonic sensor nodes's position are already know ahead. The distance between the robot and the anchor nodes can be calculated by the method provided in section II.

So, nevertheless where the robot walks in the room, it can localize its position through this WSN.

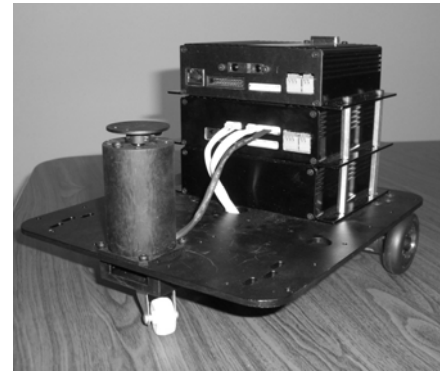


Figure.4 the EDU robot

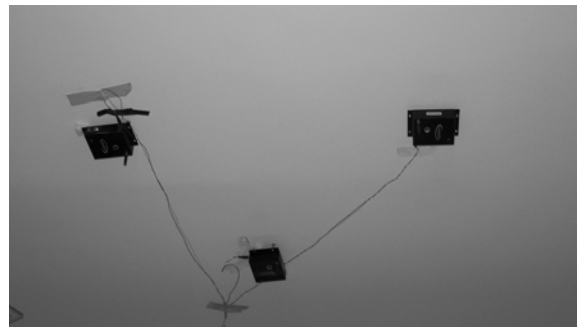


Figure.5 the anchor nodes on the ceiling

Experiment result shows the EDU robot can localize its position as a special node of the WSN.

V. SUMMARY AND FUTURE WORK

In this paper, we propose robot localization methods based on wireless sensor networks. In the WSNs, robots act as mobile nodes, so the location method for WSNs' nodes can be

used for robots. Range-based location method and range-free location method are discussed in detail in the paper.

Centroid calculation and Triangulation distance estimates as range-based localization method and Monte Carlo localization algorithm as range-free localization method are discussed in detail.

Research on Based on WSNs robot localization method is just beginning. There are many issues which can be research, such as how to improve MCL algorithm, and new location method which can cooperate robot technology and WSNs technology deeply.

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1: Step1: Initialization
2:  $t \leftarrow 0$ 
3: for  $i \leftarrow 1, N$  do
4:   sample  $l_0^{(i)} \sim p(l_0)$ 
5: end for
6:  $L_0 \leftarrow \{(l_0^{(1)}, 1/N), \dots, (l_0^{(N)}, 1/N)\}$ 
7:  $t \leftarrow 1$ 
8:  $L_t = \{ \}$ 
9: while  $|L_t| < N$  do
10: Step2: Important Sampling
11:  $C_t = \{ \}$ 
12: for  $i \leftarrow 1, N$  do
13: Sample  $l_t^{(i)} \sim p(l_t | l_{t-1}^{(i)})$ 
14: Evaluate the weight of  $l_t^{(i)}$  as  $\tilde{w}_t^{(i)} = p(o_t | l_t^{(i)})$ 
15:  $C_t = C_t \cup \{l_t^{(i)}, \tilde{w}_t^{(i)}\}$ 
16: end for
17: Step3: Filtering
18:  $C'_t = \{(l_t^{(i)}, \tilde{w}_t^{(i)}) | (l_t^{(i)}, \tilde{w}_t^{(i)}) \in C_t \text{ and } \tilde{w}_t^{(i)} > 0\}$ 
19:  $L_t = L_t \cup C'_t$ 
20: end while
21:  $L_t = \text{choose}(L_t, N)$  //choose N valid samples
22: Normalize the weights of samples in

$$L_t : w_t^i = \frac{\tilde{w}_t^i}{\sum_{i=1}^N \tilde{w}_t^i}$$

23:  $t \leftarrow t + 1$ , goto line 8

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Figure.3 MCL Algorithm